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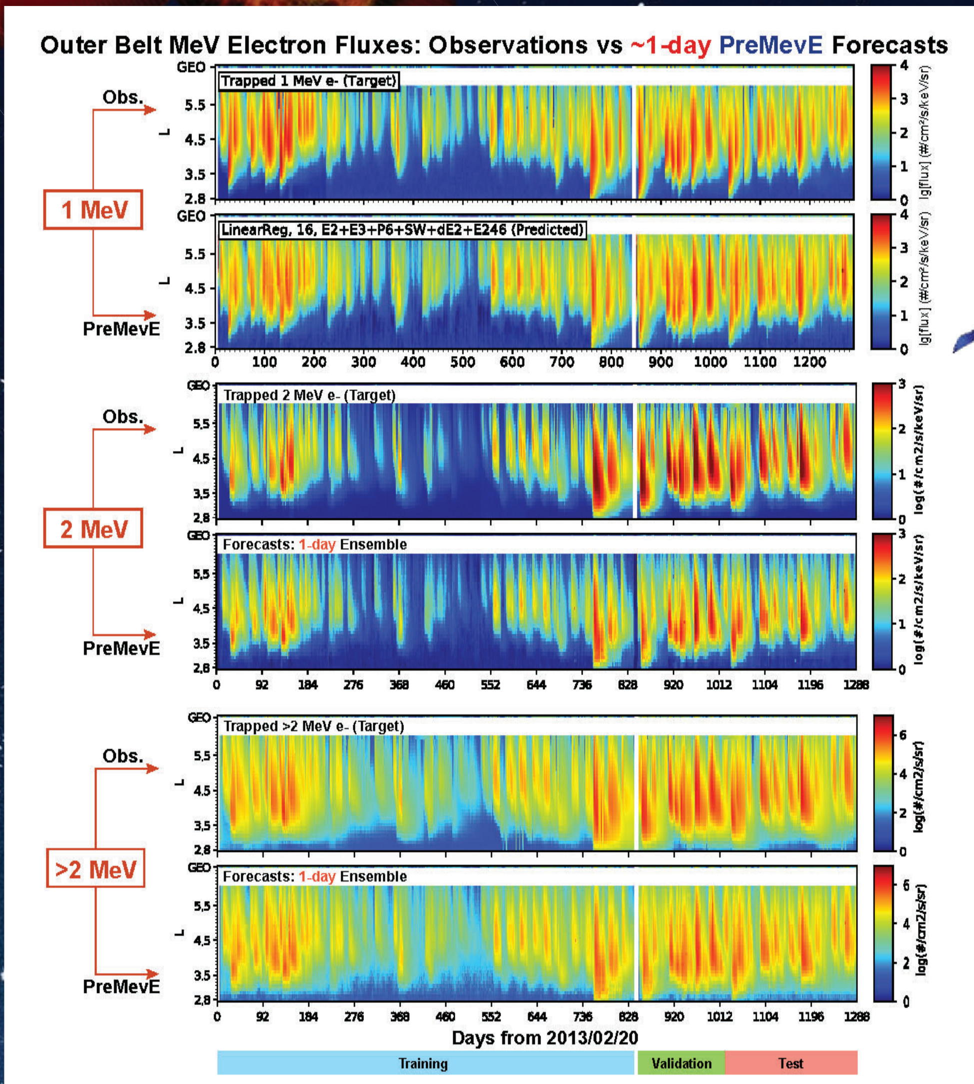
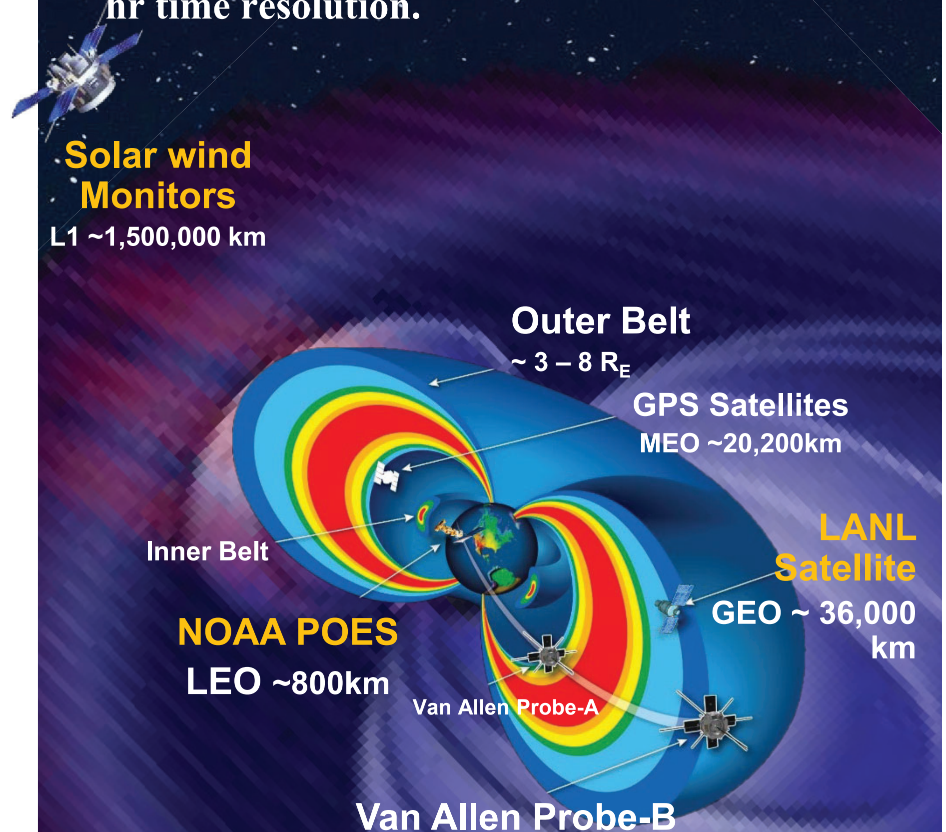
- Model Inputs: NOAA-15 electron data in LEO, LANL-01A electron data in GEO, and solar wind velocity and density data at L1 point.
- Model Outputs: Nowcasts, 1-day and 2-day forecasts of MeV electron flux spatial distributions across outer belt L-shells with a 5 hr time resolution.





PreMevE: A Machine-learning Based Predictive Model for MeV Electrons inside Earth's Outer Radiation Belt

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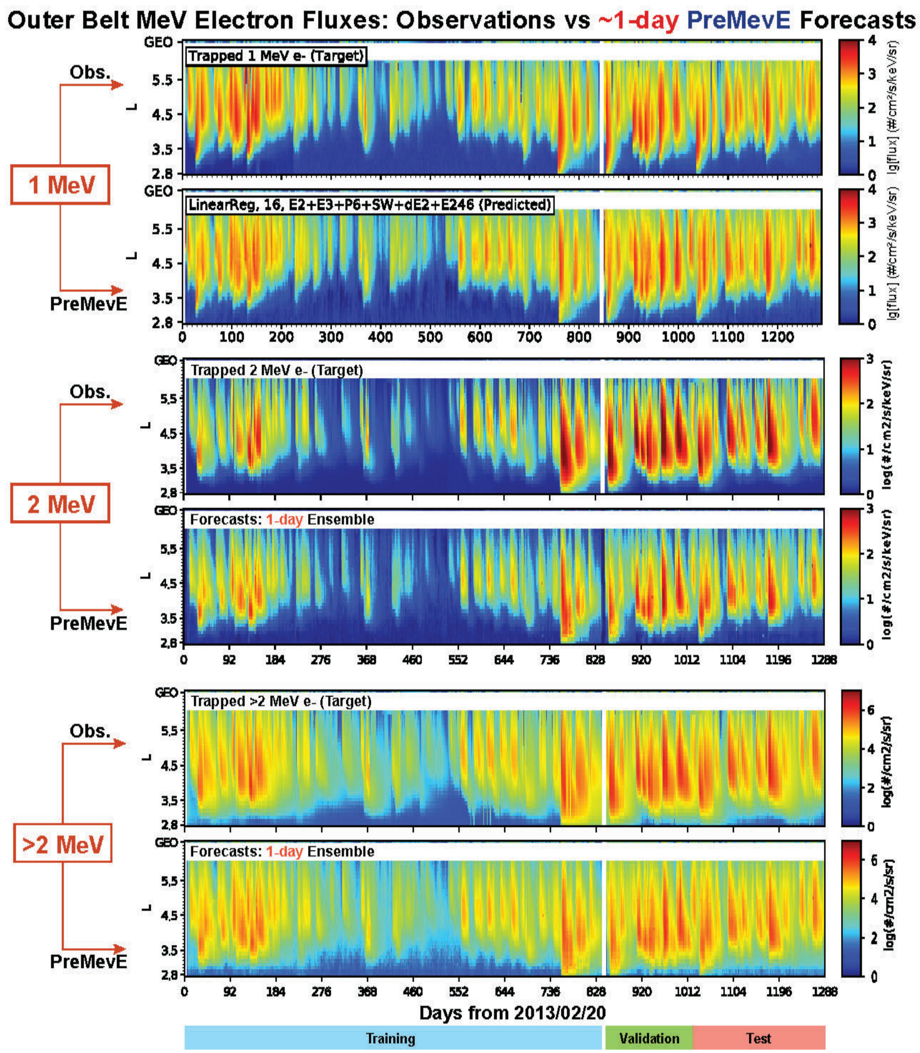
01. Overview of PreMevE



- PreMevE is a lightweight and machine-learning driven model to predict outer-belt MeV electron distributions.
- Model Inputs:
  - NOAA-15 E2, E3 and P6 electron counts in LEO
  - LANL-01A MeV electron fluxes in GEO
  - Solar wind velocities and densities measured at L1 point.
- Model Outputs:
  - Nowcasts, 1- and 2-day forecasts of MeV electron events
  - Electron spatial distributions at L-shells between ~3-7 with a 5 hr time resolution.
  - 1 MeV, 2 MeV, and >2 MeV electron fluxes

References:

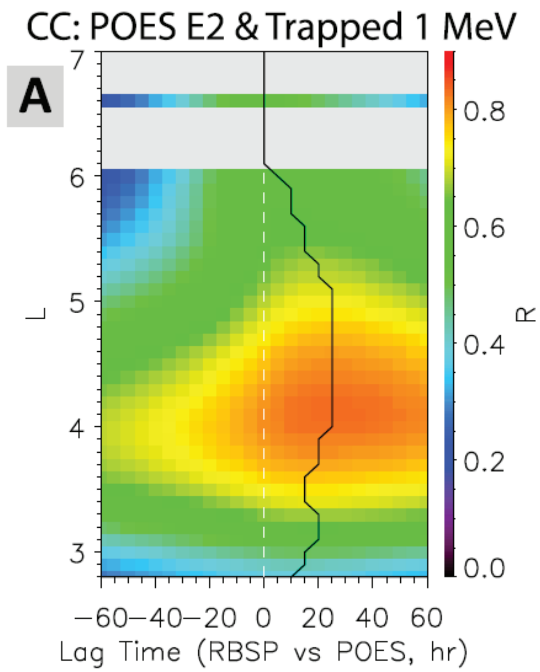
Chen, Y., Reeves, G.D., Cunningham, G.S., Redmon, R.J., & Henderson, M.G. (2016). Forecasting and remote sensing outer belt relativistic electrons form low Earth orbit. *Geophysical Research Letters*, 43, 1031–1038. https://doi.org/10.1002/2015GL067481

Chen, Y., Reeves, G.D., Fu, X., & Henderson, M. (2019). PreMevE: New predictive model for megaelectron-volt electrons inside Earth's outer radiation belt. *Space Weather*, 17. https://doi.org/10.1029/2018SW002095

Pires de Lima, R., Chen, Y., & Lin, Y. (2020). Forecasting megaelectron-volt electrons inside Earth's outer radiation belt: PreMevE 2.0 based on supervised machine learning algorithms. *Space Weather*, 18, e2019SW002399. https://doi.org/10.1029/2019SW002399

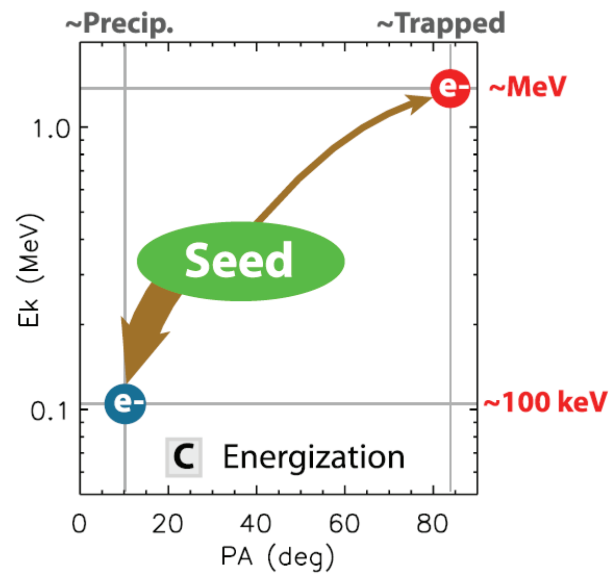
Sinha, Saurabh, Chen, Y., Lin, Y., & Pires de Lima, R. (2021). PreMevE update: Forecasting ultra-relativistic electrons inside Earth's outer radiation belt, submitted to *Space Weather*, https://arxiv.org/abs/2104.09055

02. MeV Electron Physics and Prediction

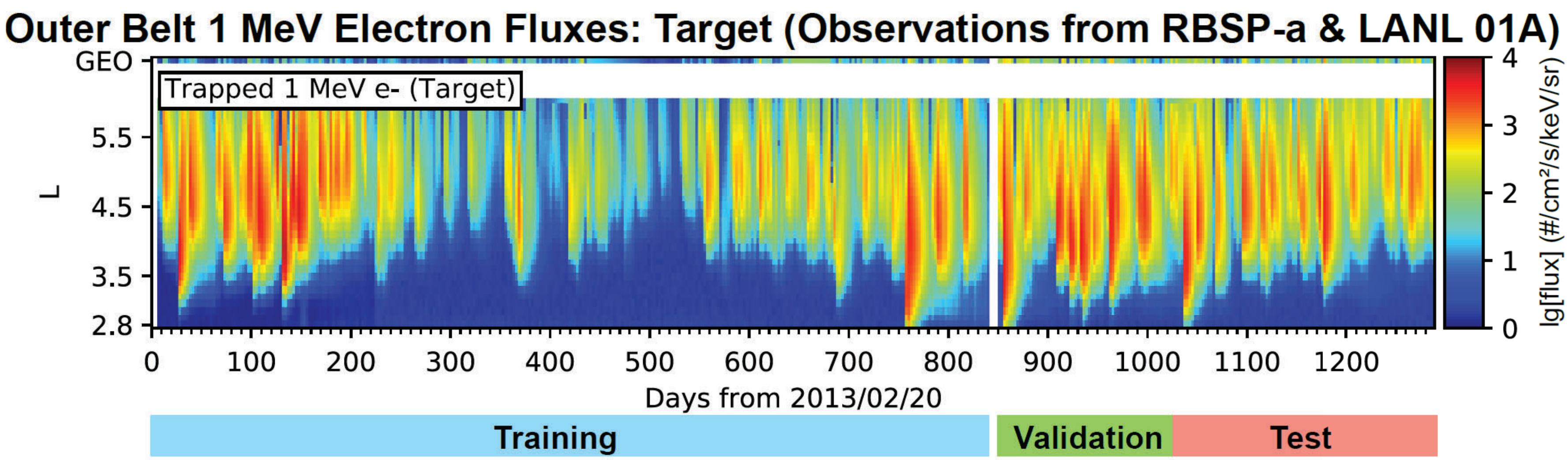


- MeV electron enhancements are related to the local acceleration from local wave-particle resonance and/or radial diffusion.
- Challenges for simulation/prediction:
  - Global distributions of waves
  - Specification of seed electron population
  - Background conditions
  - Event specific
- Our Solution:
  - Continuous measurements from long-standing space infrastructure
  - Cross-energy, cross-pitch-angle coherence discovered (left plot)
  - Power of machine-learning algorithms for linear and non-linear relationship
  - Simultaneous long-term in-situ measurements from Van Allen Probes mission

- Selection of Input Parameters:
  - Use precipitating seed electrons (POES E2) at LEO to forecast MeV electron levels during enhancements (right plot)
  - Use precipitating relativistic electrons (POES E3 and P6) to forecast MeV electron levels during decays
  - Solar wind conditions to account for radial diffusion; LANL GEO electron fluxes included to improve accuracy
- Metaphor Q: How to know the water temperature (=MeV electron level) atop a camp fire with no direct measurement? Answer: count wood ashes (=precipitation E2) and measure spilled water (=precipitation P6).

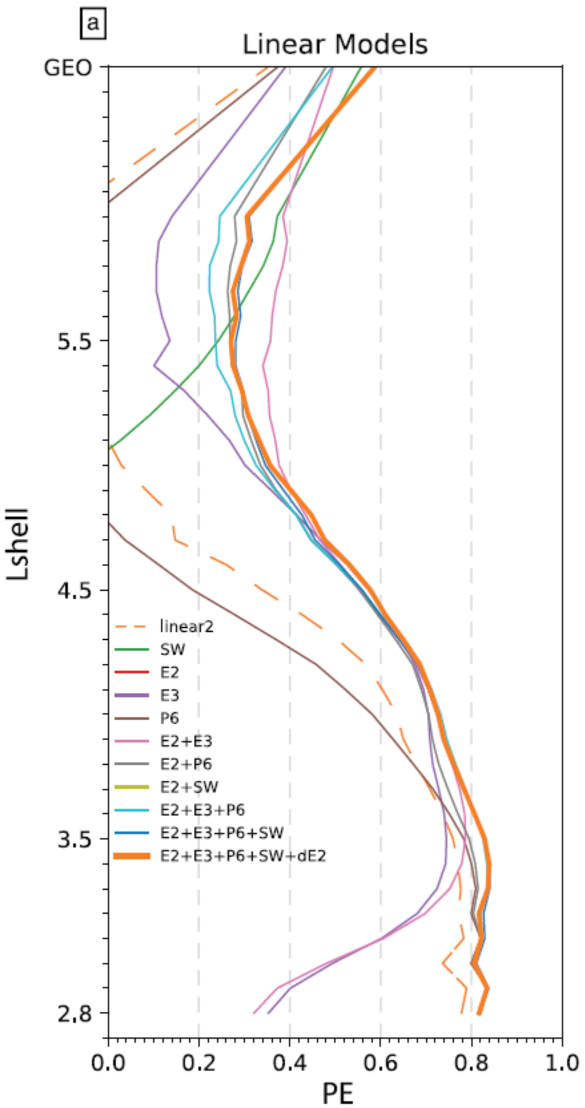


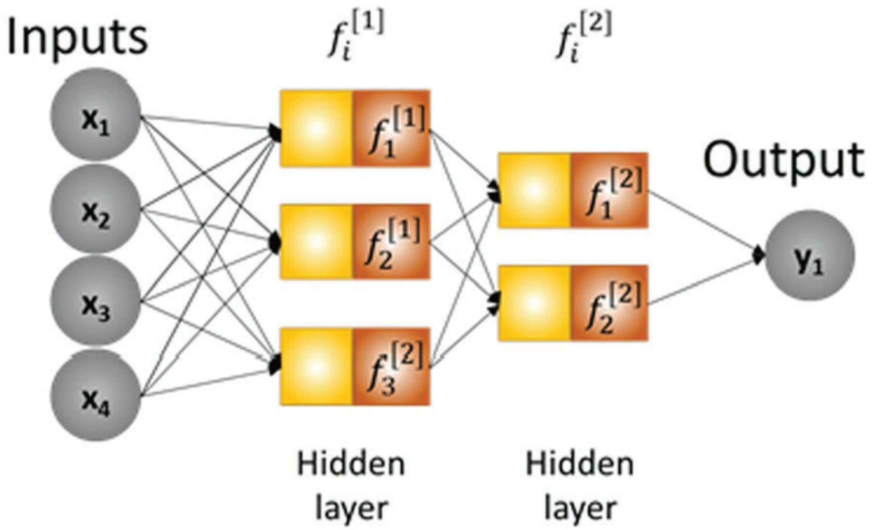
03. Model Training, Validation and Test



- Target Data: RBSP-a and LANL-01A MeV electron spin-averaged fluxes over 1289 days; 5 hourly binned and sorted by L-shells
  - Only used for model development and NOT NEEDED as model inputs
  - Many MeV events
  - Training interval: ~65% of data
  - Validation: ~14%
  - Test: ~21%
  - Model trained for individual L-shells
- Prediction Efficiency (PE) as model performance metric
  - Calculated for each individual L-shells
  - Averaged over L-shells for a single PE value for each model
  - Focus on out-of-sample PE values during validation and test periods

04. Algorithms and Input Parameter Combinations

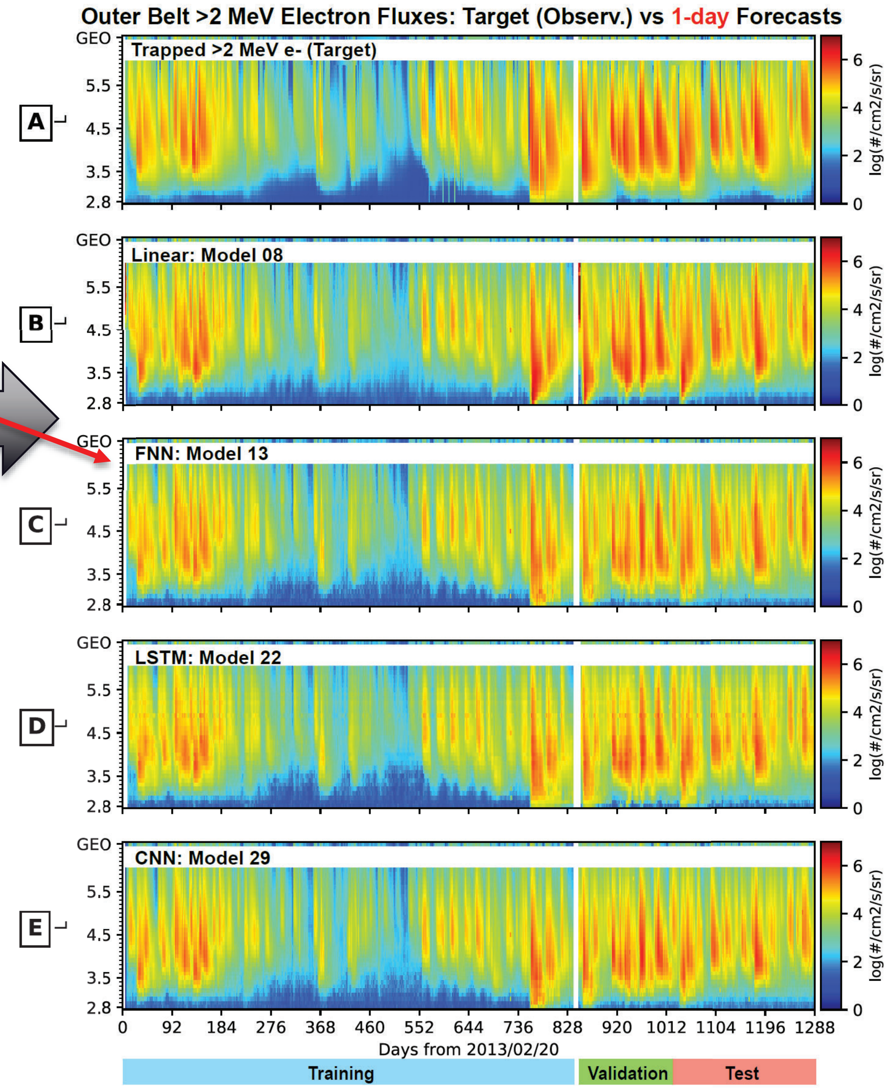




- Supervised Learning Algorithms:
  - Linear regression
  - Feedforward Neural Networks (top plot for a two neutron layers)
  - Convolutional NN (CNN)
  - Long-short-term Memory (LSTM)
- Test Input Parameter Combinations and others:
  - Window sizes of past history
  - Parameter sensitivity (left plot)
  - NN layers

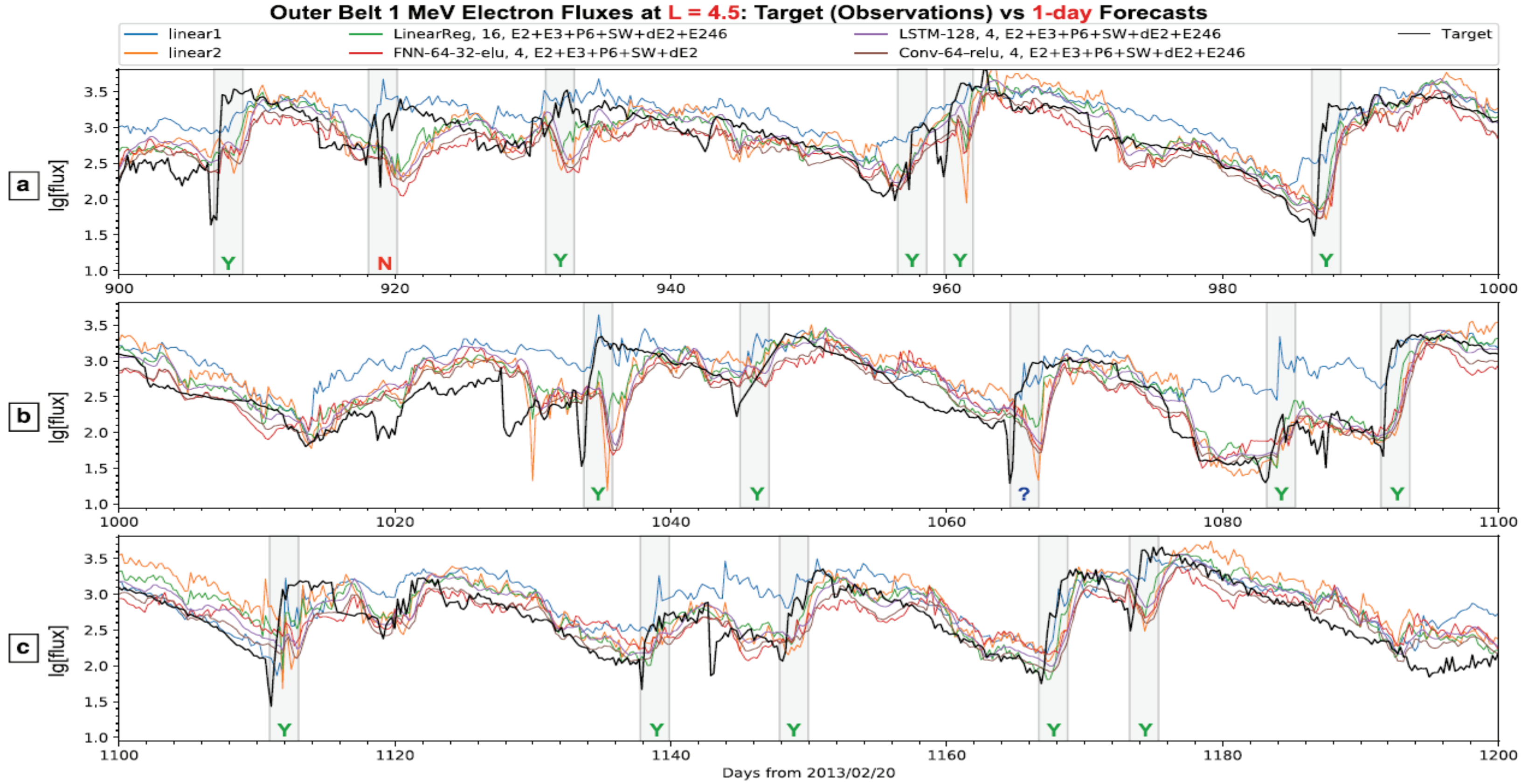
05. Model Selection and Forecasts

Index	Models	Window size	Input Parameters	PE train	PE validation	PE test	PE val + test	PE all	PE GEO val+test
1	LinearReg	4	E2+E3+P6+SW	0.712	0.108	0.454	0.414	0.707	0.621
2	LinearReg	16	E2+E3+P6+SW	0.742	0.194	0.509	0.470	0.736	0.623
3	LinearReg	4	E2+E3+P6+SW+dE2	0.714	0.112	0.461	0.420	0.709	0.622
4	LinearReg	16	E2+E3+P6+SW+dE2	0.747	0.197	0.523	0.479	0.741	0.625
5	LinearReg	4	E2+E3+P6+SW+dE2+E246	0.736	0.188	0.486	0.456	0.731	0.622
6	LinearReg	16	E2+E3+P6+SW+dE2+E246	0.763	0.255	0.548	0.509	0.757	0.625
7	LinearReg	4	E2+E3+P6+SW+SWD+dE2+E246	0.741	0.193	0.502	0.466	0.736	0.627
<u>8</u>	LinearReg	16	E2+E3+P6+SW+SWD+dE2+E246	0.770	0.266	0.568	<u>0.523</u>	0.764	<u>0.629</u>
9	FNN-64-32-elu	4	E2+E3+P6+SW	0.686	0.202	0.463	0.426	0.690	0.631
10	FNN-64-32-elu	16	E2+E3+P6+SW	0.699	0.331	0.459	0.460	0.704	0.620
11	FNN-64-32-elu	4	E2+E3+P6+SW+dE2	0.644	0.216	0.403	0.395	0.658	0.630
12	FNN-64-32-elu	16	E2+E3+P6+SW+dE2	0.716	0.319	0.511	0.488	0.720	0.603
<u>13</u>	FNN-64-32-elu	4	E2+E3+P6+SW+dE2+E246	0.766	0.404	0.566	<u>0.553</u>	0.765	<u>0.630</u>
14	FNN-64-32-elu	16	E2+E3+P6+SW+dE2+E246	0.704	0.200	0.441	0.408	0.699	0.624
15	FNN-64-32-elu	4	E2+E3+P6+SW+SWD+dE2+E246	0.713	0.266	0.456	0.446	0.713	0.646
16	FNN-64-32-elu	16	E2+E3+P6+SW+SWD+dE2+E246	0.715	0.195	0.392	0.384	0.703	0.621
17	LSTM-128	4	E2+E3+P6+SW	0.662	0.208	0.445	0.414	0.673	0.527
18	LSTM-128	16	E2+E3+P6+SW	0.750	0.366	0.537	0.521	0.747	0.581
19	LSTM-128	4	E2+E3+P6+SW+dE2	0.665	0.198	0.440	0.410	0.675	0.538
20	LSTM-128	16	E2+E3+P6+SW+dE2	0.740	0.287	0.526	0.489	0.737	0.588
21	LSTM-128	4	E2+E3+P6+SW+dE2+E246	0.700	0.282	0.472	0.459	0.706	0.535
<u>22</u>	LSTM-128	16	E2+E3+P6+SW+dE2+E246	0.781	0.401	0.545	<u>0.537</u>	0.771	<u>0.600</u>
23	LSTM-128	4	E2+E3+P6+SW+SWD+dE2+E246	0.671	0.140	0.387	0.365	0.674	<u>0.648</u>
24	LSTM-128	16	E2+E3+P6+SW+SWD+dE2+E246	0.799	0.348	0.507	0.499	0.777	0.571
25	Conv-64-32-relu	4	E2+E3+P6+SW	0.702	0.289	0.462	0.453	0.705	0.593
26	Conv-64-32-relu	16	E2+E3+P6+SW	-0.178	-3.765	-2.170	-2.333	-0.341	-0.002
27	Conv-64-32-relu	4	E2+E3+P6+SW+dE2	0.710	0.292	0.477	0.462	0.711	0.596
28	Conv-64-32-relu	16	E2+E3+P6+SW+dE2	0.186	-2.251	-1.138	-1.268	0.078	-0.081
<u>29</u>	Conv-64-32-relu	4	E2+E3+P6+SW+dE2+E246	0.719	0.324	0.480	<u>0.479</u>	0.722	<u>0.598</u>
30	Conv-64-32-relu	16	E2+E3+P6+SW+dE2+E246	0.110	-2.382	-1.334	-1.398	0.006	-0.168
31	Conv-64-32-relu	4	E2+E3+P6+SW+SWD+dE2+E246	0.749	0.285	0.497	0.477	0.742	0.566
32	Conv-64-32-relu	16	E2+E3+P6+SW+SWD+dE2+E246	0.065	-2.861	-1.636	-1.733	-0.080	0.074
33	**Ensemble: models 8 + 13 + 22 + 29**			**0.782**	**0.393**	**0.625**	**0.612**	**0.783**	**0.677**



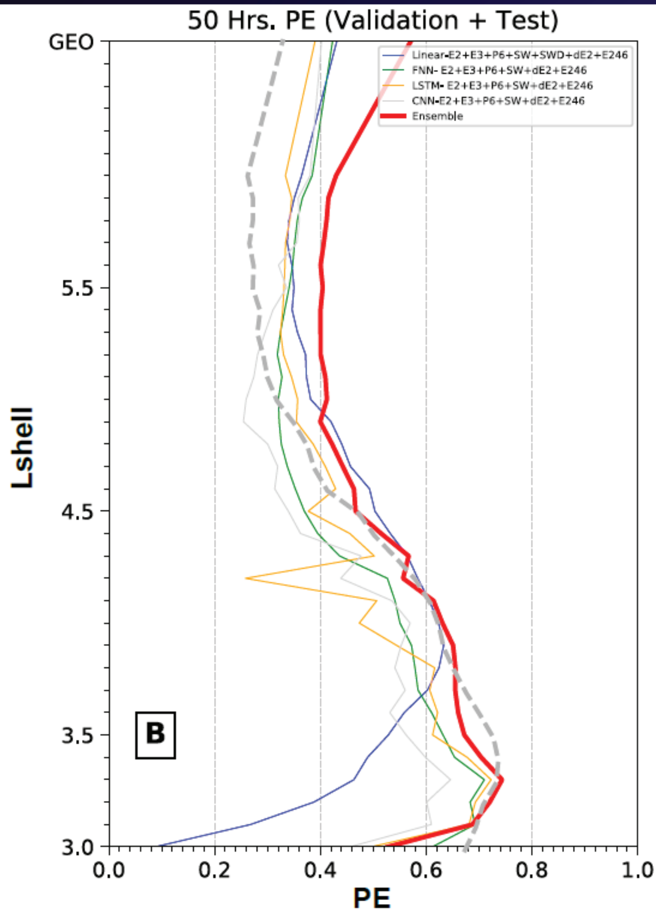
- 1-day forecasts of >2 MeV electron distributions as example
- Top Performer from each of the four categories are selected based on the highest out-of-sample PE (top table), and forecast results are compared to observations (right)
- Model performance depends on L-shells

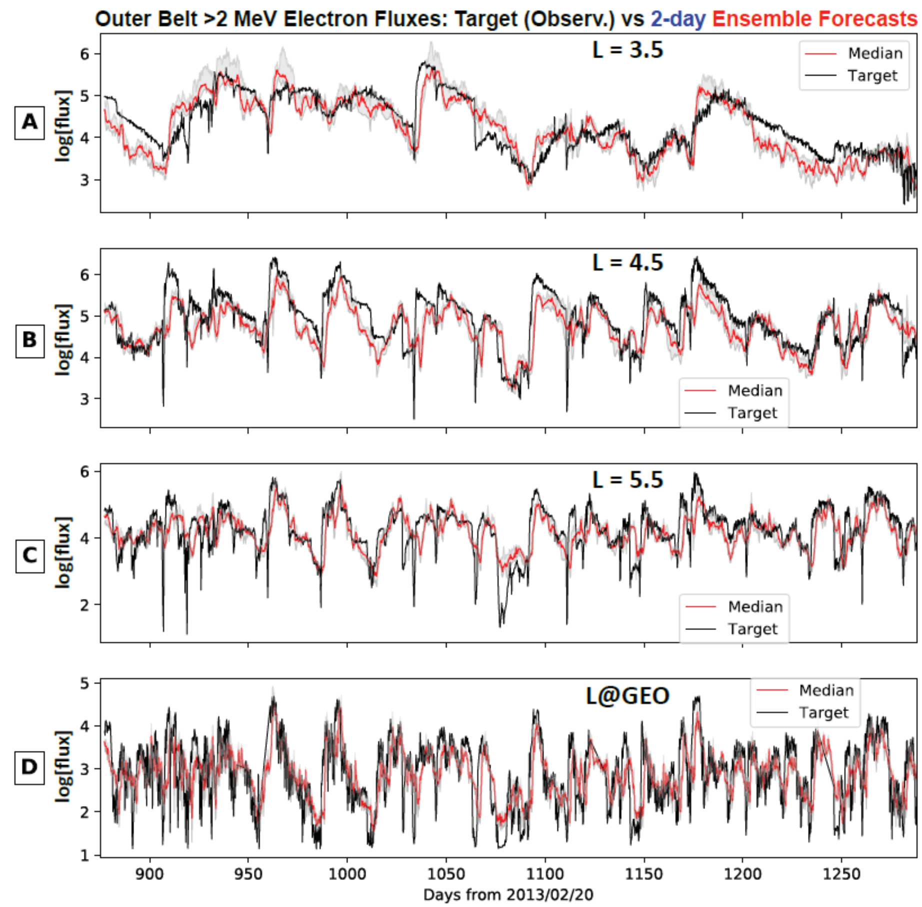
06. Details of Forecasting Results



- 1-day forecasts of 1 MeV electron fluxes at L=4.5 during the validation and test periods (days 900 – 1200) are shown as example
- Black curve is the target; top performers from each of the four categories are clustered in different colors (not the blue curve from linear filter)
- Dynamics and flux levels of 1 MeV electron events are well captured
- Most of the onsets are predicted (**Y**) by the models within the prediction window of 25-hr width.

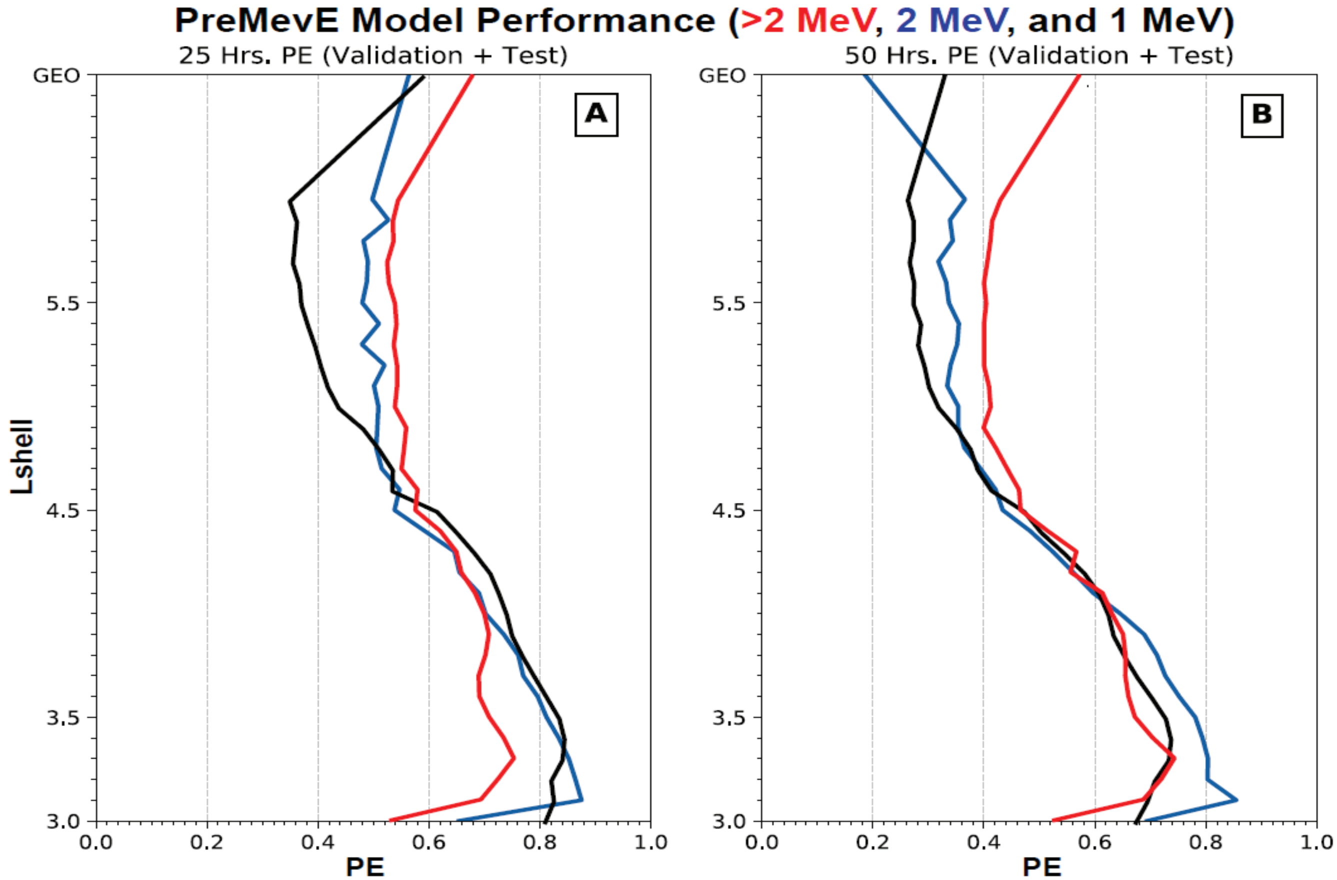
07. Ensemble Forecasting Results





- 2-day forecasts of >2 MeV e- fluxes at L=4.5 during validation and test periods are shown as example
- Not one single model outperform others at all L-shells
- The ensemble model generally has the higher PE (the red thick curve in left plot) compared to individual models
- Medians of ensemble forecasts (red curve in right plot) capture the observed dynamics (black) well.

08. PreMevE Model Performance: PE Curves



- PreMevE model makes reliable 1- and 2-day predictions on flux distributions of >2 MeV (red), 2 MeV (blue) and 1 MeV (black) electrons
- At GEO, the highest PE values are for >2 MeV electron fluxes, similar to those of REFM.
- Take >2 MeV electrons as example, the L-averaged PE has a value of 0.612 for 1-day forecasts, and 0.521 for 2-day forecasts, comparing to PE values of 0.677 and 0.572 at GEO.

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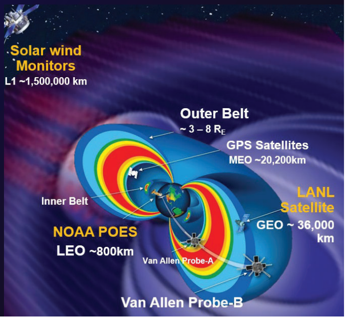
Summary and Conclusions

- Coherences (including recently discovered cross-energy cross-pitch-angle coherence) in trapped electrons are employed to develop PreMevE for nowcasting and forecasting MeV electrons in the outer belt, using inputs from LEO (POES), GEO and L1 observations. High performance of PreMevE is demonstrated by comparing to long-term in-situ data from RBSP, suggesting PreMevE be an invaluable tool for satellite operators and decision makers.

- Long-standing LEO data are used innovatively here. Existing NOAA POES constellation can play a new and powerful role in space weather remote-sensing and prediction. New opportunity for next-generation LEO (low-cost) space weather mission.

- Future direction: PreMevE may significantly improve its performance by incorporating in-situ data from such as the long-lasting GPS particle instruments.



Contact: Dr. Yue Chen: cheny@lanl.gov